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The role of AI-based technology in support of the knowledge management value activity cycle

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Abstract

The paper evaluates the phenomenon of knowledge management (KM) and its relationship to the artificial intelligence (AI) technologies of knowledge-based systems, case-based reasoning and neural networks. A knowledge value-chain (KVC) concept is established and developed into a closed loop knowledge activity cycle. This is then linked to Nonaka's knowledge spiral and related concepts. Using this framework, applied within the context of the core business processes underpinning a contemporary 'knowledge company' that is operating at the forefront of computer networking technology, the potential application of AI is investigated. The study thereby illustrates both the potential and the limitations of AI technologies in terms of their capability to support the KM process. © 2000 Elsevier Science B.V. All rights reserved.

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1. Introduction

The turbulence experienced by contemporary organisations may often be identified with the transition into what Drucker (1988, 1993) identified as 'the global knowledge society'. Within this context organisations strive to improve their competitive position through better use of knowledge, searching for new ways to harness the expertise and intellectual resources that they already possess (Hall, 1992, 1993; Edvinsson and Sullivan, 1996; Grant, 1997; Klein, 1998; Glasser, 1998) while aiming to continuously leverage them into new applied knowledge (Nonaka and Takeuchi, 1995; Boisot, 1995; Moore, 1998). However, this inevitably raises the question of how to acquire, capture, access and reuse

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knowledge throughout the organisation? This is the fundamental purpose of all knowledge management (KM) activity, which Wiig (1993) defines as:

> The conceptual framework that encompasses all activities and is required to make the organisation intelligent-acting on a sustained basis.

Several authors have analysed the role of the 'knowledge organisation' in the knowledge creating process, emphasising that successful companies are those that create new knowledge, disseminate it widely throughout the organisation and quickly embody it into new technologies and products (Nonaka, 1991, 1994; Nonaka and Takeuchi, 1995; Nonaka and Konno, 1998). This process further fuels innovation and develops lasting competitive advantage (Hamel and Prahalad, 1990).

In general, such business knowledge has been categorised as being either codified or tacit, this distinction being of critical importance strategically. Knowledge that is codified or explicit can be written down, transferred, and shared through systematic language. Consequently, even if nominally protected by law, experience suggests that such explicit knowledge may not remain a source of distinctive competence for long, as competitors strive to find ways to access or otherwise counter that which is transparently such a valuable commodity. Conversely, tacit knowledge is by nature difficult to describe and cannot be codified (Polanyi, 1966, 1998). Furthermore, tacit knowledge often has a personal quality, which makes it hard to formalise and communicate. Hence it may be so well internalised and automated that it is simply 'taken for granted' and cannot be readily articulated. It consists of that which has been learned so well that it has become routinised into distinctive knowledge, which can then be drawn upon to perform familiar tasks.

The process of knowledge creation therefore centres on the building of both the tacit and explicit forms and, more importantly, on the interchange between these two domains. This is enacted through the sequential processes of socialisation, externalisation, combination and internalisation, which is encapsulated by Nonaka and Takeuchi (1995; pp. 71–73) in the classic concept of the 'knowledge spiral'.

The complex phenomenon of knowledge is not confined to the dimensions of tacit and explicit. In Fig. 1 are displayed some other useful categorisations including declarative, procedural, specific and abstract. For example, specific knowledge is readily associated with inductive reasoning whereas abstract knowledge tends to be associated more with the deductive form (reasoning from the general to the particular, rather than the converse). A taxonomy of knowledge may thereby be envisioned in which the categories are portrayed as being dispersed as shown. Notably in some cases, overlapping and clustering of categories is evident. For example, the category of logic, which subdivides entities according to whether they are viewed as objects, attributes or values, may be generally applicable to all of the other categories. Some would also dispute whether these categories are discrete or at the extremes of a continuum, e.g. tacit and explicit (Shadbolt and Milton, 1999). It is also necessary to recognise the different types of expert and expertise associated with such knowledge. Equally important is the need to recognise the existence of different ways of conceptualising and representing knowledge through, for example, anecdote, metaphor or diagram. Finally, KM also implies recognition of the different ways in which the same piece of knowledge can be used, depending on the context and transformation processes involved in satisfying goals (achieving knowledge outputs) from information inputs.

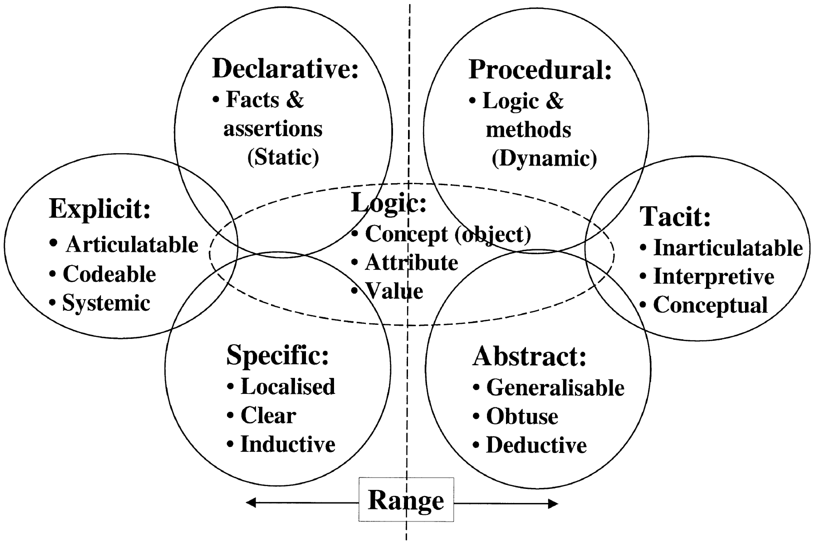

Fig. 1. A taxonomy of knowledge.

This paper is primarily concerned with exploring the extent to which artificial intelligence (AI) can support businesses in their attempts to successfully manage knowledge, within the frameworks briefly outlined above. It addresses the question as to what extent AI provides an ability to capture and organise knowledge, enabling the right people to understand it and quickly share it with all of the relevant user communities, recognising that contemporary organisation may no longer be constrained within the boundaries associated with the traditional firms of the past.

This aim is pursued through the medium of a case study featuring a contemporary 'knowledge company'. The outcome is an elucidation of the way in which key AI-based technologies may be applied within this context. This is conceptualised through the postulation of a 'knowledge value-chain model' (KVC) grounded in the data obtained during the empirical component of the study.

2. Technology and the knowledge-based organisation

Technology holds a pivotal position both as a domain for knowledge possession and creation and as a possible contributor to the knowledge proliferation and management processes (Hammer and Champy, 1993; Davenport and Beers, 1995; McQueen and Kock, 1996; Davenport, 1997; Brown and Duguid, 1998). Hence, although the primacy of the human resource, as the originator and developer of knowledge, is firmly established in the KM canon (Harrigan and Dalmia, 1991; John, 1998; Scarbrough, 1999) it is also necessary to contemplate the role and interaction of technology. This provides the potential facilitator and enabler of capabilities within the knowledge building cycle, identified by

Nonaka and others as being the core business process occurring within contemporary 'knowledge companies'.

Of particular interest, within the context of technology's role in KM, is the potential role of AI in its various forms (Lehner, 1992; Grupe et al., 1995; Turban, 1998; Wagner, 1998; Darlington, 1999). Such systems are expected to do things that have not been explicitly programmed. Consequently, AI research has been concerned with the search for programs that mimic intelligence or learning. The main categories considered herein are knowledge-based expert systems (KBES), neural networks (NN) and case-based reasoning (CBR).

2.1. Knowledge-based expert systems

This category of AI is distinguished by the characteristic that during the execution of a task or decision it can apply knowledge, or some particular skill or expertise, normally attributed to a human expert. This expertise is thereby made available to non-experts across the organisation. Following on from early work in the 1980s (Simons, 1985; Turban, 1992) there is evidence that such systems are now finding a range of applications in business (Wong and Monaco, 1995; Kunnathur et al., 1996; Mo and Menzel, 1998). For example, the survey done by Coakes and Merchant (1996) suggested that 23% of UK businesses may be using some form of expert system to support activities ranging from technical operations to strategic analysis.

The fundamentals of a classical rule-based expert system are outlined in Fig. 2. Facts (assertions) and rules (functions) constitute the 'knowledge base' of the system. This operates in close collaboration with the 'inference engine', which performs the logical manipulation and deduction of responses.

Another alternative structure for knowledge storage is the 'frame-based' approach in which data and related rules are allocated as 'objects' which, in turn, fall into classes or groups from which traits can be inherited. This can provide a simpler approach, especially if knowledge domains are naturally hierarchical. Semantic nets (Firebaugh, 1989, pp. 282–289; Shadbolt and Milton, 1999; Kuhn, 1999) provide an alternative method for hierarchically structuring knowledge. However, the adoption of frames and nets can imply that a more powerful inference engine may be required.

Rule bases may contain 'hard rules' pertaining to facts of the classic 'IF' (x) 'THEN' (y) category, but they may also contain heuristics, which can be thought of as 'localised rules of good judgement'. They may also use fuzzy logic (Zadeh, 1988; Yager and Zadeh, 1992) in addition to conventional binary logic, in situations where it is desirable to acknowledge interim states and ambiguity associated with factual conditions.[1]

During a typical sequence the rule and data selector component accesses information

[1] Fuzzy logic has the capability to accommodate ambiguity about 'state' in a way which formal or binary logic does not. Instead of the characteristic of an object being definitely either present (true), or absent (false), it permits a range of intermediate values, which may be associated with probabilities. 'Fuzzy rules' may then be applied using 'inexact reasoning', which relaxes the conventional computational constraint on the requirement of complete, unambiguous data. Fuzzy logic therefore excels in combining multi-dimensional, partially accurate, qualitative assessments to produce incrementally variable decision outcomes. In certain circumstances this may enable approximate, but acceptable solutions.

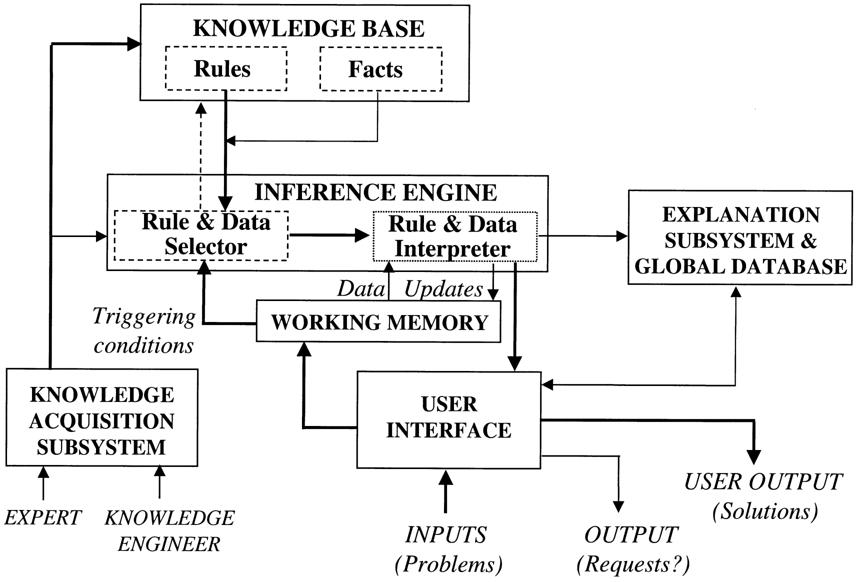

Fig. 2. The basic architecture of a knowledge-based expert system.

from the working memory. Initially, this will comprise data provided by the user relating to a particular problem and its characteristics. The inference engine then searches the knowledge base for selected facts and rules that might usefully match and augment the information already residing in working memory. It does this by interpreting the selected rules and associated data, making inferences and updating the working memory accordingly. This process can then cause new knowledge or facts to be created which can, in turn, trigger another cycle of automatic rule/data selection.

Alternatively or conjointly, the system may request further information or clarification from the user before initiating the next round of knowledge-base interrogation. This process continues until an output, acceptable to the user, is attained. Throughout, the 'global memory' tracks all rule firing events and associated data. This forms the basis of a decision audit trail that explains and documents, on request, the rationale underpinning a particular outcome. Also depicted in Fig. 2 is the knowledge acquisition subsystem, which encapsulates the domain of knowledge engineering (creation of the knowledge base and logic upon which the system depends).

2.2. Neural networks

Neural networks offer certain advantages, absent in other computer applications, including classical KBES, in that they can operate with incomplete data to generalise, abstract, and possibly even demonstrate apparent intuition (Wasserman, 1989; Sharda, 1994; Kasabov, 1999). They comprise numerous nodes that are, in some respects, analogous to the axons of the biological brain, connected together by weighted information links

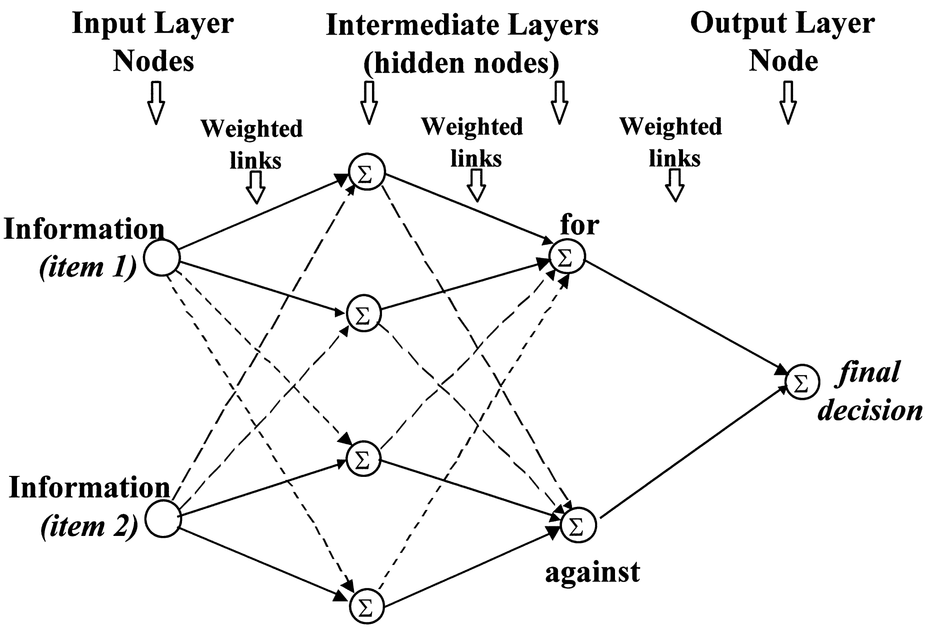

Fig. 3. The basic architecture of a neural-net-based expert system.

(analogous to the dendrites of the brain) at the interfacing synapses. Fuzzy logic could also be included within this structure, as appropriate. The result is that the output is a complex function of all of the respective inputs and their interactions. Fig. 3 presents a much simplified schematic representation of the principles involved.

The fundamental objective of the system is that it should produce outputs, e.g. decisions that are considered as good as or better than the equivalent that an expert human would have made if faced with the same set of input information. This is achieved through repetitive learning cycles in which sets of input and corresponding known outputs are applied to the system. The strength or the weightings, associated with the links between nodes, are then progressively adjusted by optimisation routines, embedded within the system, which progressively seek to reduce the error between the 'ideal answer' and the answer currently produced by the neural net. This process is repeated with different sets of training data until output performance is considered to be acceptably accurate and consistently reliable. At this stage the 'trained' system becomes potentially useful for making, or advising on, future decisions based on similar types of data input.

This approach to AI is thereby seen to be completely different to that which underpins rule or frame-based expert systems as there is no embedded explicit knowledge base or associated rule set, only a set of assumed empirically derived relationships between data. Consequently it is not claimed that NNs possess knowledge about particular structures or situations. Their function is simply to provide a 'black-box' transformation of input data to output advice or action, based on previous 'learning experiences'.

2.3. Case-based reasoning

Case-based reasoning is another alternative AI technology which, like the NN, performs operations based on raw data (past cases and associated solutions) rather than on stored explicit facts and rules (Rubin, 1992; Allen, 1994; Cunningham and Bonano, 1999). However, unlike the neural net the system does not attempt to manipulate specific inputs or seek relationships between them. It simply selects and displays what it considers to be potentially helpful stored cases, to match problem descriptions that are subsequently submitted to it in the form of a new case. This process can proceed on an iterative basis involving questioning and response of the user. Upon completion, the content and results of successful new cases may be appended to the existing database, for future use. The disadvantages with such systems include the heavy associated administrative load that can arise and ultimate dependence on the human infrastructure (as with the other forms of AI).

2.4. AI and tacit knowledge: the management challenge

Although impressive claims for neural nets have been made, such systems are also subject to a number of substantial reservations, especially if compared to the power and performance of real biological brains, operating within the context of KM. Challenges faced include the appropriation of nodes to match the 'requisite variety' of the problems likely to be encountered, in service. Also the need to provide an adequate training database (size and representativeness) may prove to be a formidable challenge which if not adequately met, might result in sub-optimal selection of weightings with a resulting reduction in fidelity. Furthermore, being based purely on a set of empirical data, there is no guarantee that the network will perform satisfactorily if exposed to situations markedly different to those that comprised its 'learning experiences'. Unlike a human, it does not have additional sensitivities that can make it aware that its environment has changed. This can result in unrealistic extrapolations being made.

Hence it is apparent that neural nets are strictly data manipulators and storage/presentation devices, respectively, and do not contain a knowledge base, in the classical sense. Consequently there is no direct attempt to embed explicit knowledge in the form of facts or rules. Neither is it possible to trace the logic of a particular decision through the labyrinth of such logic. The system merely replicates weighted calculations which it knows from experience, gave a good answer last time. It is thereby possible that such systems could mimic tactic knowledge but there is no embedded understanding such as occurs in the case of human reasoning.

By comparison, CBR does contain a form of knowledge base in the form of its recorded case history. However, this does not give rise to hard facts; neither are there embedded rules and it is again unlikely that such systems could contain tacit knowledge, as envisioned by Nonaka and Takeuchi.

Conversely, as Hendriks and Vriens (1999) point out the noun 'knowledge' is common to both the KBES and KM disciplines. However, the emergence of more recent KM concepts succeed much of the pioneering work on AI and KBES, and were consequently not available to influence such developments. Neither do AI and KBES concepts appear to be particularly prominent within the KM literature of the late 1990s. This may be because the emphasis, in developing KBES, has usually been strongly technological whereas KM's origins are much closer to the philosophical and human resource dimensions.

Furthermore, strictly classical rule-based expert systems rely, ideally, on assumptions of structure, certainty, rationality and linearity which are oriented towards solutions based on best choice between clearly available alternatives. This is in sharp contrast with the domain of KM which assumes a world based on uncertainty, subjective meaning, belief and faith. These characteristics are best represented in the concept of 'tacit knowledge', which has been established as being of such importance in the building of sustainable competitive advantage. Consequently, it appears that the particular characteristics of tacit knowledge may prove to be a significant impediment to its implementation within the context of AI technology.

Consideration of the availability, capability and limitations of AI-based technologies, as outlined above, led to the case-based research presented below. This was aimed at interpreting the business process requirements of a KM company and elucidating the potential role of AI within this context.

3. Methodology

A phenomenological methodology was considered to be most appropriate to the objectives of the current study (Sauders and Thornhill, 2000). This reflects the grounded theory approach of Glaser and Strauss (1967) in which theory evolves in a cyclical process featuring both inductive and deductive reasoning. An ethnographic study of the core business process in a typical knowledge company thereby gave rise to the postulation of a descriptive model, which was then assessed within the framework provided by existing theory (in this case provided by consideration of available AI capabilities, matched against the demands of the KM phenomenon).

The research was based on data gathered through interviews and multiple visits to Bay-Point's Technical Centre in Valbonne, France. This company is a subsidiary of Bay-Networks Inc. which, with over 7000 employees in 90 countries, has established a leading position in world-wide internetworking. The company provides a complete line of products that serve corporate enterprises, service providers and telecommunications carriers. Products offered include frame and ATM switches, routers, shared media, remote and Internet access, IP services and other networking management applications. These are all integrated through the organisation's 'adaptive network strategy'.

Bay-Networks sees its purpose as being:

> To revolutionise the way people work, learn and play by eliminating the constraints of distance and time

(Bay-Networks internal source, 1998).

The company operates a single source, open-standards-based technology that provides service and support for high-performance availability, interoperability and networking requirements at all levels. These range from enterprise and service provider backbone environments to branch offices and remote users.

3.1. Knowledge management at Bay-Point

The company proclaims awareness of, and commitment to, the concept of KM with excellence in both external KM services, and internal KM practices, being seen as of prime importance:

> Sharing your expertise or your skills allows you to share the related tasks and to clear time to develop new skills

(Bay-Networks, internal source, 1998).

Within this framework, the Valbonne operation provides professional services and consultative expertise on optimisation of network performance, thereby supporting the wider business throughout Europe. Its on-line information services provide full access to the company's technical information library, latest software upgrades and secure on-line case management. It thereby functions as one of several similar call-centres located around the world serving different time zones. The intention is to ensure that customers realise the full potential of their information networks as a competitive differentiator in the marketplace. The Valbonne call-centre's mission statement is thereby defined as:

> To realise ease-of-doing-business by providing our partners and customers with one single point of contact that has both ownership and responsibility to fulfil customer requirements, up to complete satisfaction

(Bay Networks internal source, 1998).

The core business process of customer enquiry handling is organised through first-, second- and third-tier engineers supported by various knowledge bases which are continuously updated and maintained in order to acquire and store the full range of expertise available within the company. In principle, all of this information is available to every engineer to help answer clients' questions or problems. However, difficulties existed in that this information had been cumulatively stored, over a period of five years, in a number of different servers, thereby constituting a diffused knowledge base. The system was therefore very complex and relatively slow given that engineers need to find answers quickly while connected on-line, with clients. Furthermore, in order to quickly find a solution, the engineer needs to be able to identify the right keywords in the description of the problem. Hence he/she needs to 'feel' the problem, and to use his/her intuition and tacit knowledge, in order to provide a satisfactory response. Notably, it appears that in this context, technology potentially provides a useful support tool but does not provide a total solution.

3.2. The knowledge value-chain concept

The ethnographic component of the study featured an analysis of the business processes typically enacted when responding to call-centre enquiries. Tracking the path from raw information retrieval through to useful knowledge production and capture thereby identified five discrete but inter-linked value-adding phases as follows:

Find. This applies to documents and other sources containing the required raw information. This stage involves the presentation of general queries such as full-text searching over large document collections, or presentation of specific queries such as keyword searching. A core requirement is that the process must be achieved in a timely and convenient fashion.

Filter. This stage involves screening the information from the selected documents and other sources to extract only what is relevant to the particular knowledge task at hand. This includes the application of successively narrower criteria to rank, categorise and filter documents in order to locate those sections that contain the information required.

Format. This stage contains a preliminary assessment of who will need access to the information obtained. The aim is to provide sufficient variety to achieve effectiveness of communication for all who are, or could be, affected. The process typically includes text formatting, summarisation, presentation of graphs, charts, spreadsheets, multimedia, etc. Formatting should also allow users to identify important relationships within the information much more easily than they could have done using simple text.

Forward. The formatted results must then be forwarded to the person or group of people that can use them most effectively. This involves deciding on, and then delivering appropriately formatted content through the most appropriate media. Options include reports, email-summaries, personal database updates, attached documents, intranet pages, fax, telephone, pager, etc. Some iteration to the Format stage, or even to the 'Find' stage may be required if additional potential users are identified during the process.

Feedback. This stage closes the knowledge loop. As an organisation acquires experience in converting information to knowledge, it develops an ability to function more effectively as future knowledge needs arise. The final stage of feedback thereby provides the ability to adapt the first four stages to new circumstances.

These stages may be considered to collectively constitute a KVC model, similar to that proposed by Steier et al. (1997), in which the Find, Filter, Format, Forward stages can be thought of as representing a forward pass through the chain. This process converts accumulated information into knowledge which, in turn, gives rise to organisational learning, through the feedback linkage which continuously updates the 'corporate memory'. This final phase is particularly important with respect to the concerns expressed by Davenport and others, regarding the issue of knowledge-base maintenance. For example, it is acknowledged that knowledge evolves continuously (Barthelme et al., 1998), which implies that if expert knowledge is to be retained in the longer term and knowledge erosion is to be avoided (Hendriks and Vriens, 1999) then it is essential that this final stage is not omitted. However, in practice, such omissions can too easily occur in the face of the daily pressures of responding to information needs and processing client requirements; hence the importance of formally including this final stage in the KVC sequence.

3.3. Benchmarking knowledge-management support technology

This stage of the study also identified a clear need to facilitate the engineer's work by devising better ways of using the information available on the various servers. The problem faced, was the homogenisation of different knowledge bases to constitute, in effect, a virtual 'single server', capable of delivering, quickly and accurately, the information required. Clearly, the possession, sharing and successful management of this knowledge was a distinctive source of potential competitive advantage to this company.

However, without appropriate technological support, it was doubtful whether this potential would be realised to optimal effect. It therefore appeared sensible to question whether AI-based technology could play a role in assisting this particular KM process?

In a search to identify appropriate technology within the context of this study, a benchmark study was conducted, in collaboration with Bay-Point staff, featuring a number of products available at that time. These included BACKWEB 4.0 (BackWeb Technologies), FULCRUM KNOWLEDGE NETWORK 2.0 (Fulcrum Technologies Inc.), KNOWLEDGEX ENTERPRISE 1.0 (KnowledgeX Inc.) and SEARCH 97 INFORMATION SERVER 3.1 (Verity Inc.). The evaluation was primarily performed using the forward pass criteria of the KVC outlined above, applied within the context of assisting the three different levels of engineers who deal with customer enquiries. For each product, a typical enquiry sequence was evaluated with special attention being paid to the way in which the respective products addressed the functional criteria identified in the KVC model.

From the analysis it was observed that collectively, the four individual products were all capable of providing some support to this particular organisation, efficiently capturing the right information and subsequently delivering customer value. For example, FULCRUM KNOWLEDGE NETWORK proved particularly effective against the 'Find' criterion whereas KNOWLEDGE ENTERPRISE scored highest against 'Filter' and BAKWEB against the 'Forward' criterion. Notably none of the products proved individually optimal in all respects. Furthermore, being essentially search engines, these products appeared to operate exclusively within the domain of explicit knowledge. Consequently there was no real evidence that they were able to capture the tacit knowledge that clearly featured so prominently in the core business process of this organisation (which is primarily concerned with converting tacit knowledge possessed by its engineers, into explicit knowledge which can then be communicated to clients). However, much of the true value of this knowledge lies in its 'taciticy', which inherently implies problems in formalisation and communication, as discussed earlier. Clearly this tacit dimension is closely associated with the human resource dimension, rather than the exclusively technological ones, as tacit knowledge is usually shared and nurtured in face-to-face dialogue. Hence, as Prusak (1998) puts it:

> Although IT is a wonderful facilitator of information transmission, distribution and storage, it can never substitute for the rich inter-activity, communication, and learning that is inherent in dialogue. Knowledge is primarily a function and consequence of the meeting and interaction of minds. Human intervention remains the only source of Knowledge generation.

Consequent to the analysis of these contending technologies it was deduced that additional functionality would need to be included to fully accommodate the human contribution to the process. This implied a need to find a suitably powerful search engine which would effectively fulfil the KVC criteria but also facilitate tailored human interaction to tap the tacit knowledge base that was known to exist within the organisation.

3.4. The extended knowledge value-activity cycle model

Concerns about the limitations of 'pure AI' technology's ability to fully address the

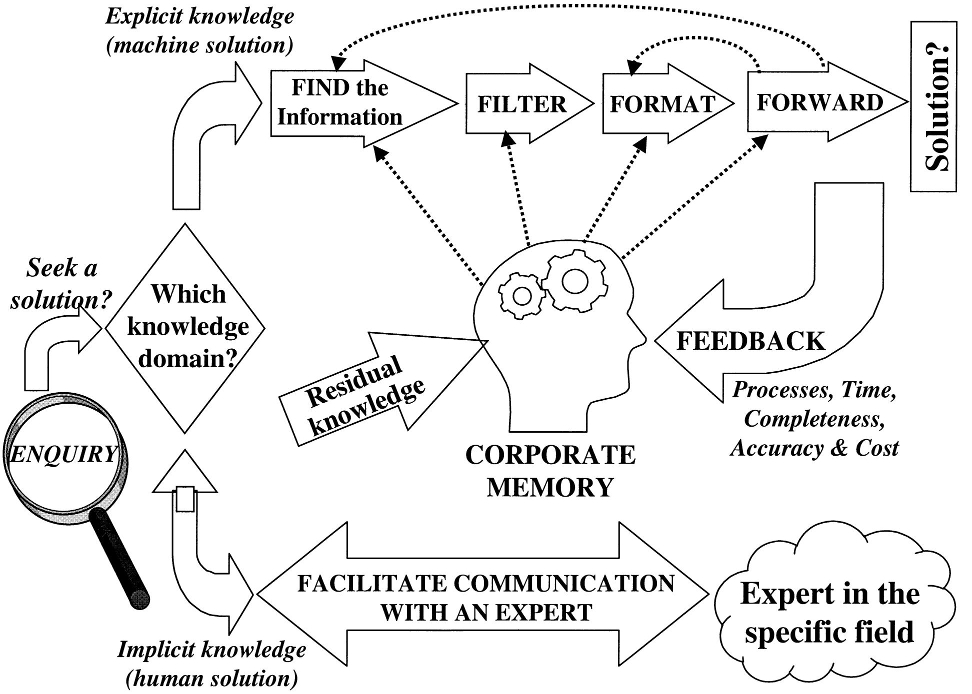

Fig. 4. The extended knowledge value-activity cycle model.

requirements of the KVC model and its associated tacit knowledge implications, prompted investigation of the category of technology known as intelligent assistant systems or intelligent agents (Boy, 1991; Armstrong, 1992; Wasson and Akelsen, 1992; Herrman et al., 1998). Typical manifestations include 'active document technology' to support the processes of explaining and advising in response to customer enquiries (Gaines and Shaw, 1999). Such systems may combine aspects of AI with human intelligence, rather than attempting pure AI solutions. This can result in enhanced problem-solving capabilities and an improved likelihood of user acceptance. The benefit of such co-operation may be epitomised by the expression IA > AI (Brooks, 1996). This implies that intelligence-amplification by machine and mind can outperform a mind-imitating AI system working by itself. The combination of formal, explicit knowledge in the machine, and the non-formal, tacit knowledge of the users, can thereby result in problem-solving capabilities which surpass either one of these components acting alone. The implication of super-imposing this additional facility upon the proposed value-chain model, as introduced earlier, may be depicted schematically by the 'extended knowledge value-activity cycle (EKVAC)' depicted in Fig. 4.

An application that appeared to provide a good fit with the requirements of the EKVAC, within the context of the Bay-Networks benchmarking study, referred to above, was located in the form of *Dataware Knowledge Management Suit* (DKMS). This product is based primarily on data-warehousing technology and provides users with a single point of access with which to tap corporate knowledge assets (Szuprowicz, 1997; Gallegos, 1999; Sullivan, 1999; Thompson, 1999). However, it also contains features emanating from classical AI. It incorporates a rule base and provides access to multiple information databases (including the Internet) through its search engine, which is supported by data-mining technology capable of structuring the results of searches. One of its databases identifies experts according to their previous creative contributions (parallels with CBR). The system also accommodates 'meta-data' (information about information), which gives contextual support that helps transform information into knowledge. This, together with its capacity to contact human experts implies that it goes some considerable way towards enabling access to tacit, as well as explicit knowledge when responding to customer enquiries.

Hence if the knowledge requirements solicited during the enquiry are explicit in nature then a solution can emerge during the forward sweep through the respective KVC stages, identified in the upper section of Fig. 4. Conversely, in the event that a strong tacit or implicit dimension is encountered, and a solution cannot be found by this route, the system automatically switches the enquiry to an appropriate expert, as depicted in the lower section of the schematic. Having successfully retrieved the required information a solution is then presented back to the enquirer. At this stage the system also attempts to record the transaction in its knowledge bases for future use (thereby encapsulating the feedback function of the EKVAC).

3.5. Illustrative example: the client enquiry process at Bay-Point

The following example is based on a typical scenario within the Bay-Point KM context. Typically a customer or client contacts a front-line engineer with an enquiry about a particular piece of equipment. For example, a customer may suspect that a particular router or an autosense-hub product, embedded in a particular integrated data and telephony network configuration, is performing less than optimally. A preliminary search is made through a 'browser-like front end' using parameters leading to the presentation of relevant documents. KBES principles may be usefully deployed at this stage, firing rules, seeking knowledge and presenting interactive questions to the engineer and his/her client. However, if similar cases have been previously encountered and recorded then these too may be called upon to provide an additional knowledge source (thereby invoking CBR principles).

Having found and filtered the required information, the system must then present this in an appropriate format to match the requirements of the original enquiry. The way in which documents are presented could be weighted, as occurs in a conventional search engine. However, use of AI technology (e.g. neural nets, NN) can enhance this facility. Upon being presented with this information the engineer may also be provided with meta-information (KBES may also be appropriate in this role). Included with this meta-information might be the reason why these particular documents have come to exist in the first instant. This may be due to previous cases having already been encountered (reference to CBR technology again). Associated with such meta-information is the name and location of the author. Hence, if necessary, this 'expert' (for example a grade 2 or grade 1 engineer)

Table 1
Potential technology deployment in the EKVAC at Bay-Point

Stages	Application example	Potential technology deployment
Find	Possible solutions to a network problem?	KBES, NN, CBR
Filter	Which documents are most relevant?	KBES, NN
Format	How to match user requirements?	KBES, NN, CBR
Forward	Inform potential stakeholders	KBES, NN
Feedback	Update corporate memory	KBES, CBR

may be consulted directly, thereby enabling more in-depth, tactic knowledge transmission processes to be activated.

Having uncovered knowledge relating to and answering this particular enquiry it may transpire that there are implications for other technical or marketing staff within the company or for external customers or suppliers. In this case some further formatting may be required before forwarding to other interested parties. The whole transaction will also require to be recorded in appropriate format at an appropriate location within ‘corporate memory’ (the feedback function).

Clearly the respective AI technologies possess different strengths with respect to the various stages in the EKVAC model, as outlined above. A suggested matching scenario may thereby be envisioned as summarised in Table 1.

4. Discussion

A fundamental objective of this paper is to assess the role and limitations of AI-based technology within the context of the KM phenomenon which is playing such a dominant role in management thinking at the present time. The paper’s logic, as encapsulated in this discussion section, therefore attempts to pull together the related but discrete themes of Nonaka’s knowledge spiral, business process analysis and AI technology. The primary ‘academic deliverables’ arising from this process are the concept of the extended knowledge value-activity cycle, as encapsulated in Fig. 4, and an assessment of the potential role and limitations of AI in serving the EKVAC concept. These have emerged through the grounded research approach featuring analysis and synthesis of existing nominally discrete but related concepts coupled with observation and refinements arising during the case-study phase.

Interest in these phenomena is inspired primarily by the observation that while short-term competitive advantage may arise as a result of access to specific knowledge and understanding, lasting knowledge-based competitive advantage can only be sustained if organisations are deeply involved in knowledge creation on a continuous basis. Knowledge is therefore identified as the key resource that can distinguish an organisation from its competitors. The task of KM is then to deliver value by developing and exploiting knowledge-based core competencies and the associated key business processes in which they are embedded.

‘Furthermore, it follows that such knowledge oriented processes may be amenable to leverage by the appropriate use of technology including AI. However, it has been argued that, in principle, certain forms of knowledge are not susceptible to explicit formulation and must therefore remain within the tacit domain (Prawitz, 1988; Dreyfus, 1992). This is in accordance with Polanyi's observation on tacit knowledge, which notes that it cannot be represented by a set of articulated rules or algorithms. The problem is especially apparent in situations where tacit knowledge is embodied in individual perceptions, beliefs and values. The distinctive characteristics of the knowledge being managed, as differentiated in the taxonomy diagram, Fig. 1, is then particularly important as it is the dynamic interchange between tacit and explicit knowledge that continuously sources new knowledge creation, in the spiral envisioned by Nonaka and Takeuchi (1995).

Tacit knowledge also implies a freedom to react instinctively or to act in a way which may appear, according to accepted wisdom, as illogical. Knowledge may be unique to the mind, often involving highly personal characteristics based on life's empirical experiences rather than pure logic and objective facts. Hence knowledge cannot always be separated from that which is 'the human total'. Such characteristics clearly contravene the conventional principles of computer science, including AI. At worst, excessive preoccupation with AI-based technology may even pose a distraction from critical issues such as culture, leadership, and other human resource dimensions. Such reservations are very neatly summarised by Davenport and Prusak (1998) who note that:

> The shortcomings of artificial intelligence should heighten our appreciation for human brainpower.

The question thereby arises as to what extent the AI-based technologies, explored here, may be able to contribute to KM in contexts such as Bay-Point's?

4.1. The potential contribution of KBES

Although the tacit knowledge issue and its associated difficulties have been brought to prominence by the current interest in KM, the problem is not new. For example, it may be argued that the KBES associated discipline of knowledge engineering has, since its inception, always had to accommodate the problems of accessing and embedding tacit knowledge (Feigenbaum and McCorduck, 1982, pp. 79–80; Sandberg et al., 1997). Hence much of the theory and practice of knowledge engineering (Hoffman et al., 1995; Cooke, 1998; Studer et al., 1998; Mykytyn et al., 1998; Menzies and Van Harmelen, 1999) over the decades, has been concerned with finding the means to extract and codify implicit knowledge.

Knowledge engineering necessitates the acquisition and codification of both the factual knowledge and the procedural logic of a human expert. This generates a hierarchy of difficulty depending on proximity of the knowledge base to the tacit domain. Consequently, declarative knowledge is usually the easiest to process while heuristics may require greater subtlety. Also, the logic, or actual reasoning process applied by the experts themselves, is likely to be highly tacit in nature. This presents a major difficulty, both in terms of articulation by the expert and interpretation (capture and coding) by the knowledge engineer. These issues have long been recognised as the 'Feigenbaum bottleneck' phenomenon (Firebaugh, 1989, pp. 617–618). Consequently, Shadbolt and Milton (1999) suggest that the knowledge engineering tools and methods (i.e. the process) that, in many cases, have been used very successfully to develop 'intelligent systems', may now have a particularly important role to play in KM, as distinguished from the actual 'intelligent systems' (the products) themselves.

Consequently KBES are most appropriate where diagnostic and prescriptive responses are required. In this case the embedded rules attempt to capture the reasoning in the mind of the human expert while the knowledge base corresponds to the facts residing in the human expert's memory.

It has also been argued that in comparison to humans, the classical KBES's communication format is rigid and unable to respond to vague, or unusual questions and answers, or 'body-language', etc. Practical difficulties are also encountered in maintaining the knowledge base (Davenport, 1996; Davenport and Prusak, 1998; Prusak, 1998). In its pure state, neither can a KBES learn independently by experience, or restructure its knowledge to assess the relevance of new facts. For example the concept of 'common sense', which is an immensely powerful facility potentially possessed by humans, is unattributable to a KBES. Similarly, the concept of analogical reasoning (Bouchon-Meunier et al., 1994, 2000) remains a major challenge. Finally, KBES are unable to understand the rules or recognise the limits of the relatively rigid set of facts contained in their databases. Neither are they capable of breaking rules, under exceptional circumstances, in the way that humans can, if they recognise some inherent implausibility.

In summary, although it is accepted that knowledge can be embedded in organisational processes, networks, patents, or document repositories, which can readily be incorporated into a KBES, it must also be recognised that tacit knowledge presents particular challenges.

4.2. The potential contribution of CBR

Knowledge engineering is concerned with eliciting rules and facts from experts. However, in practice, these human experts often reach conclusions by a somewhat different mechanism, drawing inferences from both positive and negative experiences accumulated in the past. This process is analogous to CBR. Previous cases may be recalled, adopted, checked for appropriateness and then applied. These new cases may subsequently be added to the repository of retained knowledge to create a form of database constituting problem descriptions, pertinent questions, proposed solutions, consequences and a convenient means of indexing and retrieving cases that suggest a solution to current problems. CBR may be particularly appropriate in domains where theory is acknowledged to be weak, in which case influences and interactions are poorly understood. Although they do not have an explicit knowledge base (in the sense of KBES) such systems do need to have a defined vocabulary, a database of cases, a similarity metric to identify which cases are to be reused and in some situations, a mechanism for adapting solutions.

When used to support appropriately skilled knowledge workers such as Bay-Point's engineers, they may have much to offer, especially when supported by meta-information and possible linkage to human expertise, as depicted in the EKVAC model. Similarly, application of CBR, in such cases, is often limited by the unavailability of suitable case-data in a readily usable form, for example at start-up. The 'seed case base' must be sufficiently large and of adequately transparent relevance to encourage users to consult and augment its contents. Consequently, CBR does not necessarily overcome the problems inherently associated with the 'knowledge bottleneck' phenomenon as epitomised in knowledge engineering. In order to circumvent unattractive resource overheads, CBR systems are therefore ideally required to be based on available databases or other electronic sources.

There is also a need for each case to be defined in terms of its scope (i.e. type of problems referred to), sources of information storage, and the format and quality of the information contained. The architecture of representation must also ensure that cases are called up appropriately. Finally, some form of verification and validation is desirable to test ultimate usefulness and reliability. Hence, in summary, CBR may go some way towards addressing the tacit knowledge dimension since the explicit knowledge contained in the database can be retrieved and interpreted using the tacit knowledge endowed in the human. This may be less rigid than the formal rule-based approach of KBES.

4.3. The potential contribution of NN

CBR works through an indexing process, based on a matching algorithm. Conversely, neural nets apply statistical weightings to predict outcomes. In one sense they can produce new 'synthetic knowledge' but they do not contain a knowledge base or memory that is analogous to the factual basis or inference mechanisms of KBES. Neural nets also ultimately require their inputs to be presented in numeric form so that they can then be subjected to the learned weighting algorithms. This is in contrast to KBES and CBR, which both accept symbolic inputs. However, providing that such inputs can be presented in appropriate form, neural nets may have much to offer.

Furthermore, NNs appear to work more analogously to the brain (or indeed to an analogue computer) than a digital computer. In this sense, they appear to have much potential within the KM context. They are capable of finding a solution based on categorising a multi-dimensional input vector and thereby selecting an appropriate output vector, as occurs, for example, in handwriting recognition. Hence a particular problem may not be identical to, but may be recognised as being reminiscent of, something similar. Such actions are clearly potentially useful within contexts such as those depicted at Bay-Point.

Systems based on NN are also capable of profiling users to enable information to be targeted at certain individuals according to their preferences, interests or previous enquiries. Interest groups can be established and records updated every time the system is accessed. In this way, the system continuously learns about its user base and there is no need to laboriously fill in new preference lists as new interests develop; the system does this automatically. New information is thereby made available to members of an interest group and could, if necessary, be actively 'pushed' in their direction, using ordinary email if required, rather than waiting to be 'pulled' by request.

Having identified patterns in text or other sources, such systems can also create a 'concept agent' that goes on to search for matches in other sources. Agents may thereby be trained, by users, to fine tune performance. Such systems can also decide how to categorise and where to store new documents. Employee expertise profiles can also be created automatically depending on pattern of usage.

Despite their apparent potential, applications in situations such as Bay-Point's appear to be relatively sparse, at the present time, although commercial business oriented products are now beginning to appear (Clarke, 1999). The longer-term impact of such products, for KM companies such as Bay-Point, remains to be seen but the future appears promising, as long as expectations are tempered in accordance with the limitations expressed herein.

4.4. Summary

On balance, it has been argued that AI-based technology, on its own, does not provide a unique solution to organisational KM needs. It still does not substitute for human intelligence and possesses only a limited capability to address the issue of tacit knowledge. However, it may still serve as a facilitator of the human interaction which remains the primary source of knowledge generation, thereby providing a mechanism to support and enable an organisation's KM processes. It is thereby accepted that AI potentially creates the means to capture, retrieve and transmit data and information more effectively and quickly. It is also capable of manipulating raw data and producing higher-order information and, as such, potentially contributes to the development and leveraging of knowledge in new and effective ways. Furthermore, the creation of hybrid systems comprising combinations of rule-based expert systems and NNs may offer access to embedded knowledge coupled with an ability to function in the partial absence of certain data. Such systems may also exhibit a capacity to learn and subsequently improve their performance over time.

In addition, the knowledge base can also contain examples drawn from recorded experience, thereby reflecting the CBR approach. This may further extend the capability of the system and potentially relieve the acquisition bottleneck problem associated with classical KBES. This may be particularly useful in supporting applications where the theoretical base is less than substantive. Finally, it is worth reinforcing the point that these technologies are not mutually exclusive and appropriately matched hybrid forms may have much to offer.

The potential and limitations of the respective approaches, in support of KM, are typified in the Bay-Point case. For example, it was noted that the organisation's knowledge-base had evolved and was currently being maintained in several isolated systems. This, in turn, had led to the notion of 'knowledge silos' that often provided adequate local information but were not easily accessible or visible by the wider community of potential users within the organisation. Consequently, there existed a need for a comprehensive business process perspective, facilitated by flexible tools to collect, organise, filter and then selectively deliver what is, in effect, a complex and highly diverse body of knowledge. This represents a classic example of the knowledge value-cycle concept in action and also illustrates the potential contribution of the three respective AI-based support technologies.

5. Concluding comments

Knowledge management (KM), strongly emphasising the human perspective in organisations, is now openly acknowledged as the key to competitiveness, in many contemporary companies. However, organisations still need information technology, possibly including aspects of AI, in order to leverage, facilitate and share knowledge. While it is clearly important to recognise the fundamental limitations of these technologies, especially with respect to the management of tacit knowledge, they may still provide an effective supporting role in underpinning the complex dynamics of KM processes. This said, current assessment suggests that these limitations are very fundamental and are likely to prevail for the foreseeable future.

Within the context of the present research, the processes involved in supporting KM, with technology, have been made explicit through the medium of the extended knowledge value-cycle model. This envisages the potential role of AI and the human/machine interaction as the focal aspect of 'the total system'. This perspective has been illustrated in the case of Bay-Point, a classic knowledge company in which complex operations, located within a manufacturing-service continuum, have to be managed through the medium of highly trained engineers working with networked knowledge bases. Improving this knowledge cycle, and the intelligence embedded therein, was perceived as a distinct source of potential competitive advantage, albeit one that at the outset of this study, was currently less than fully optimised owing mainly to the complexity therein. Notwithstanding this reservation, it is evident that hybrid AI-based products are now becoming available that are capable of delivering this functionality, in practice, to service the requirements of knowledge companies such as Bay-Point. Such an approach shows potential for gaining improved customer loyalty and differentiating providers from their competitors, through effective and imaginatively configured support technology.

In summary, the extended knowledge value-cycle model, emerging from this research, encapsulates the core processes involved and may thereby be seen to embody the following core characteristics:

- It is fundamentally customer focused and business process oriented.
- It enshrines the sequential and iterative knowledge-spiral concepts of Nonaka's model.
- It can be embedded with advanced, AI-based, hybrid technologies as they develop.
- It embodies experience and understanding derived from the knowledge engineering literature.
- It accommodates the various knowledge categories including human centred tacit knowledge.

Finally, it is suggested that there remains substantial scope for further research and development potentially leading to a new breed of intelligent assistant systems that fully reflect the processes and requirements depicted in the extended knowledge value-cycle concept. This prioritises the perspective of KM to provide a framework for the predominantly technological orientation that has traditionally underpinned much of the AI domain. Such work could take the form of qualitative research to further assess the level and category of AI currently or potentially employed in KM applications and the capability of the EKVAC model to capture this usage. For example, developing the 'grounded theory' approach leads naturally into an evaluation of the model's potential within the context of other KM domains such as Design Engineering and Marketing. Such research could also potentially be extended into a quantitative stage to examine managerial preferences and estimates of time, costings and gains associated with the respective stages in the knowledge value cycle. The concluding goal, at the current stage, is that this particular conceptualisation will prove useful as a focus for further discourse amongst those who may wish to apply and extend these ideas within wider empirical contexts.

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